Proposed Title of the Study:

Examining Consumer Interaction with Artificial Intelligence Tools: Chatbot and Voice Assistants

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1 Chapter 1: Introduction

1.1 Introduction and Background:

Artificial intelligence (AI) is disrupting the traditional way businesses are interacting and communicating with customers (Verma et al., 2021). The way customers search for information and build opinions is challenging old theories and creating a huge avenue to understand how customer interactions are changing in the arena of marketing and customer service (De Bruyn et al., 2020). AI as a tool is becoming popular in the daily life of the consumer. AI is believed to transform customer experience on digital platforms by understanding the user behaviour through past data, building knowledge on such data to serve the customer better by recommending products based on their previous choices and similar choices made by other users (Puntoni et al., 2021).

AI is currently being used in many fields. To quote a few examples, in online shopping recommendation agents are used to help customers' decision making (Häubl & Trifts, 2000). In the area of finance AI applications are helping banks to improve their asset management, operation efficiency and fraud detection (Fethi & Pasiouras, 2011). In the healthcare sector, it can help in detecting cancer (Esteva et al., 2017; Leachman & Merlino, 2017).

Artificial intelligence (AI) is defined as "machines that mimic human intelligence in tasks such as learning, planning, and problem-solving through higher-level, autonomous knowledge creation" (De Bruyn et al., 2020). AI has been around for many years of advancement for example Eliza, a natural processing tool, was created in 1966 to simulate a conversation with a human (Weizenbaum Joseph, 1966). A few other successes in this field led to increased interest and funding until it was criticized subsequently and reduced to the level of an "experienced amateur" in games like Chess and Go. With the increase in big data, and advances in natural language processing it has become possible for AI to enter business arenas (Haenlein & Kaplan, 2019). Artificial neural network used in solving complex tasks and deep learning are popular forms of AI, that help in speech recognition, and image recognition and are widely used in smart speakers and self-driven cars. Predictive analytics is used in marketing to help marketers forecast future marketing actions such as customer churn (Kumar et al., 2019).

1.2 AI Conversational Tools in Marketing

Holz et al., (2009) have classified conversational agents on the reality – virtual continuum. At the extreme reality end comes robots that are physical and converse with users using natural language processing, followed by mixed reality conversational agents these are called social robots (Čaić et al., 2018). In the category of virtual assistants are; embodied conversational agents and disembodied conversational agents such as chatbots, Siri, Alexa etc towards the virtual end of the continuum.

AI-based chatbots and voice assistants have conversational capabilities where they can converse with customers in human language either through text or voice mode (Holz et al., 2009). These tools offer convenience in terms of quick access (Cardona et al., 2019), personalization (Zumstein & Hundertmark, 2018), and reduced waiting time for customers (Ostrom et al., 2019). They are able to track the likes of the customer and provide recommendations based on past history or searches done by customers and help in gathering information (Kumar et al., 2019). Chatbots are deployed by companies for their live chats on the website for frontline or customer support (Adam et al., 2020; Xu et al., 2020), and on social media sites (Araujo, 2018).

Voice assistants such as Alexa, Siri, and Google assistants converse with the customer through a voice mode (Hoy, 2018). They can be used with devices such as speakers, and smartphones through voice commands. Voice assistants initially started with routine tasks such as play music, set a reminder, and now extending their services for searching products, recommending and ordering products (Klaus & Zaichkowsky, 2020).

1.3 Motivation For The Study

The chatbot market is expected to reach US $ 1250 million by 2025 (Statista, 2019). Company executives will quickly adopt the technology due to the immediate benefits of reduced cost and quick service (Gartner, 2019). Similarly, the use of voice assistants is expected to triple to 8 billion by 2024 (Gartner, 2015; Juniper Research, 2018; PwC, 2017). A recent report from WATconsult (2022) has indicated that voice shopping is growing in India and is likely to reach 168 million shoppers.

Despite the growing optimism around AI conversational tools i.e., chatbots and VA, managers are still unsure about the areas where they could confidently automate using AI

technology (De Bruyn et al., 2020). There is a dearth of studies in the area of customer perceptions and preferences to use AI tools (Davenport et al., 2019; van Doorn et al., 2017). Specifically in the context of chatbots what are the tasks consumers would like to use a chatbot has not yet been researched (Dwivedi et al., 2021; Larivière et al., 2017). Furthermore, Shahab et al. (2021) have mentioned mere exposure effects and other consumer behaviour theories have not been studied in the context of modern technology and marketing. Similarly, in the context of another conversational AI tool, VAs what are the areas where consumers would like to interact with voice agents remain unexplored MSI (2020). Additionally, Moriuchi (2019) has suggested that an experimental study could help in understanding how customers interact with VAs for specific tasks and specific product categories.

To fill the gap gathered from the literature, the study focuses on conversational agents such as AI-based chatbots and voice assistants that are being used by companies to assist customers either in information search, purchase, or customer support.

Interaction with a chatbot can be in the form of a conversation to search for information about a company or a product (Adam et al. 2020, Xu et al. 2020). Companies have deployed chatbots for customer support to answer queries as they are quick, can function all around the clock, and are convenient (Van Pinxteren et al., 2020). Despite these benefits, they are not successful everywhere (Longoni et al., 2019; Zhang et al., 2021). Customers may opt to use it in certain situations and may require human help in others (Larivière et al., 2017). Therefore, it is important to understand the areas where customers prefer to use chatbots. What are the areas where chatbots could satisfy customers when looking for answers to their queries? Areas in which intention to use is high could be the areas where chatbots could help customers independently to solve their queries.

Voice assistants (VAs), growing popular amongst users. VAs can assist customers in a purchase transaction, allowing quick information search, recommending products through an algorithm, and making life easier for a customer by saving time and effort e.g., Alibaba's Tall Genie, and Walmart Voice Order using Google Home. Alexa is also capable of conducting a product search and helping in a purchase transaction. This skill has been recently added to Alexa in the Indian subcontinent (Alexa for shopping in India, 2020).

The way the two tools are used by customers is different. Chatbots are widely deployed in customer service and customer support to answer queries (Behera et al., 2021; Følstad &

Skjuve, 2019). VAs are generally used for searching information (Moriuchi, 2019). The convenience offered by a VA is enhanced due to a voice command. The interaction with voice is likely to be different from the interaction with a chatbot hence it is necessary to deal with these tools separately. Therefore, two separate studies are conducted to understand customer interaction with AI tools viz., chatbots and voice assistants.

Accordingly, the study looks into customer interaction with AI tool through;
Essay I: Role Of Task Characteristics; Task Complexity And Time Pressure In Preference To Use Chatbots For Customer Service
Essay II: Role of presentation format and product involvement in preference to use a voice assistant.

Essay I;
Essay one consists of two studies that look into customer interaction and examine areas in which customers prefer to use a chatbot (Larivière et al., 2017; Vimalkumar et al., 2021). This essay is placed in chapter 2. The first section is introduction that gives a background about chatbots, and includes literature review. Section 2 explains the theoretical background and hypothesis development. Section 3 gives an account of research methodology and section 4 includes results and analysis. As customers interact with chatbots in the form of questions and answers the study looks at customer queries as a motivation to use chatbots.
While deploying chatbots for answering customer queries companies use chatbots differently. The exposure to a chatbot is also likely to influence customer's choice to use a chatbot. To examine the first research question, task technology fit theory is used and customer queries are classified based on task characteristics such as task complexity and time pressure. The second research question focussed on understanding what is the best way to resolve these queries to result in higher adoption of chatbots. For this research question the study uses mere exposure effect and decision points theory to understand consumer behaviour after exposure to chat interactions. Decision points are manipulated to demonstrate the effect of resolving customer queries in the same window.
Communication with a chatbot is likely to have a significant effect on satisfaction, intention to use (Mero, 2018), perception of competence (Longoni & Cian, 2020), and engagement (Holtgraves et al., 2007; Moriuchi et al., 2021) hence these variables are captured as dependent variables for this study.

Essay II focuses on customer interaction with voice assistants. This essay is discussed in detail in chapter 3. The content of chapter 3 are on the same lines as chapter 2, Introduction and literature review, Theoretical background and hypothesis development, Research methodology and results are given in section 1, 2, 3 and 4 respectively. Customers use VAs to search information for about products (Klaus & Zaichkowsky, 2020; Mari et al., 2020). Customers' search for product information is influenced by product involvement. VAs announce the product details (search results) in their voice. Some VAs are embedded in devices that have screens and therefore they can present the results in voice and visual format. The presentation helps customers in gathering information and making a decision. Thus, it is proposed that product involvement and presentation mode influence the trust and usefulness of a VA and further influence the intention to use and intention to purchase products using a VA.

Theoretical contribution, Managerial Implication and limitation are included in chapter 4.

2 Chapter 2

Essay I: Role Of Task Characteristics; Task Complexity And Time Pressure In Preference To Use Chatbots For Customer Service

2.1 Introduction

AI-based chatbots are increasingly being used by companies to provide customer service through various platforms such as live chat platforms on company websites social network messaging, and mobile apps (Adam et al., 2020; Schuetzler et al., 2020). A chatbot is a software-based system that is designed to interact with a human in their language, using natural language processing and AI technology (Griol et al., 2013; Shawar & Atwell, 2007). Improvements in natural language processing, chatbot dialogues and designs, and communications have led to enhanced customer experience (Hagberg et al., 2016). Chatbots offer advantages such as uninterrupted service, and personalization for customers (Tsai et al., 2021). Companies found chatbots useful in customer service as they helped in reducing wait time through self-service and automation, and allow quick information dissemination (Ostrom et al., 2019).

Banks in India are using chatbots for live chat support on their websites and mobile apps e.g., HDFC Bank- chatbot EVA, Axis Bank -AHA, ICICI Bank - iPal. A good example of quick and untiring service is HDFC Bank's chatbot, EVA, who answers over 50,000 queries daily (Firstpost, 2017) and is likely to extend digital services to provide support to rural customers (S. Roy, 2021). Similarly, food delivery companies such as Zomato, and Swiggy use chatbots for customer support.

Industry reports indicate that chatbots will be able to reduce substantial labour costs for companies (Juniperresearch, 2018), and will be handling around 25% of customer service and support operations by 2023 (Gartner, 2019).

Chatbot technology is not new in the western world and is studied extensively. But it is fairly new in India (Trivedi, 2019) and only a few studies have been done so far. There are 834 million internet users in India (TRAI, 2021), making India second largest country with internet users in the world (Staista, 2022). A growing number of internet users and an increasing number of companies deploying chatbots indicate an increase in chatbot usage.

Use of chatbots in customer service Customers have access to multiple channels for service but online customer service offers advantages such as time saving, convenience and availability as per the customer. These qualities of online customer service have significant influence on customer satisfaction and enhanced brand loyalty (Colwell et al., 2008; Negash et al., 2003). In a service context response time, quality of response and connection are important elements of satisfaction (McLean & Osei-Frimpong, 2017; Mitussis et al., 2006; Verhoef et al., 2009). Live chat assistance was found to be helpful for customers in decision-making by providing timely guidance and assistance when searching for information (Chattaraman et al., 2012). AI enabled chatbots used in live chat are faster in their response and hold a very promising area of customer support (Adam et al., 2020).

Users often display a different behaviour when interacting with the chatbot. Especially, it was found that conversation content and nature of communication changes with chatbots as compared to a similar situation when interacting with humans, for example, users communicated for a longer time with shorter messages, compromised vocabulary and in some cases greater profanity (Hill et al., 2015). Chung et al., (Chung et al., 2018) found that customer's perceptions of having received quality communication enhanced eservice satisfaction with chatbots in the luxury segment. Early studies on chatbots advertising effectiveness on social media (Facebook messenger) found that when chatbots were perceived to be helpful and useful consumers found them less intrusive and advertising messages received through these chatbots as effective (Van den Broeck et al., 2019). Study by Araujo (2018) found that when the design of the disembodied chatbot on social media (Facebook messenger) had human-like cues such as name, language and style, interaction with such a chatbot had positive influence on perception of social presence, attitudes, satisfaction and emotional connection with the company. Adam et al., (2020) found that presence anthropomorphism cues in AI based chatbots helped in getting the users to comply with the chatbot request such as leaving their name and contact details. When compared AI customer service with human customer service, in the context of financial institution, it was found that customers perceive that AI customer service had greater problem-solving capacity and displayed greater intention to use that form of customer service for low-complexity tasks. As against high-complexity tasks where they perceived human customer service to have greater problem solving capacity (Xu et al., 2020). In a series of experiment by Longoni and

Cian (2020), have found effect of recommendation and coined it as word-of-machine effect. When the tasks were of utilitarian nature people prefer AI recommender and for hedonic, they resisted it by showing preference to human recommender. Customers found augmented intelligence, artificial intelligence used in combination with human executives, helpful when AI recommender was used in hedonic task and human recommender in utilitarian task. In a 3x3 experiment Balakrishnan and Dwivedi (Balakrishnan & Dwivedi, 2021) found that human to machine interaction influenced cognitive absorption more than human to human interaction.

Chatbots are interactive, and friendly and allow customers to chat in a natural way (Chung et al., 2018). Users agree to comply to the chatbot's request due to the anthropomorphic cues (Adam et al., 2020). AI-enabled chatbots used in live chat are faster in their response and hold a very promising area of customer support (Esch, Cui, & Jain, 2020). However, this is only one side of the story. Other researchers have found that customers may not be comfortable

when it comes to using chatbots for specific personal use (Cheng et al., 2021). Despite the benefits offered by a chatbot, such as time-saving along with an interactive and quick response, some reports have indicated that chatbots also face problems like high failure rates (Longoni et al., 2019). Tsai et al., (2021) have found that in embarrassing contexts, chatbots were not as effective as human employees in soliciting self-disclosure. The presence of contradictory findings in the literature makes it difficult for a manager to decide which task could be given to a chatbot and which should be allocated to human service agents. Moreover, it is important to understand the usage of chatbots from customer's viewpoint (Luo et al., 2019). Previous literature has indicated that there is a lack of understanding in the area of customer interaction with AI tools (Brandtzaeg & Følstad, 2017; Davenport et al., 2019; van Doorn et al., 2017). Therefore, a further probe is needed to understand areas where customers would prefer to interact with the chatbots (Larivière et al., 2017; Vimalkumar et al., 2021). Luo et al. (2019) have pointed out that in future, customers may decide to interact with a chatbot over a phone based on task complexity and customer preference. Customers interact with the chatbot in the form of questions and answers (Adam et al., 2020; Sivaramakrishnan et al., 2007) or customer queries. Hence it is important to understand for what kind of queries customers would prefer to use a chatbot.

When put together, these views will be contradicting and very confusing, especially for a manager who wishes to use chatbot service for front-line or customer service (De Bruyn et al., 2020). What kind of queries can be handled by the chatbot employed, that can ensure satisfaction, and trust in the efficacy of the transaction and is at least on par when compared to a service employee in the same service? It could also happen that customers would prefer chatbots in some transactions as compared to others. For example, will the customers prefer to use a chatbot or prefer to connect with a service employee when the query is urgent? As a manager, it would be a risky affair to automate service without knowing in which area will automation with the help of a chatbot be effective and readily adopted by the customer.

Chatbots provide answers, solutions, and guidance to customers through text or audio mode or both (Rzepka et al., 2021). The text is designed in question-and-answer format. These posted queries eventually resolve customer doubts and, accurate answers help customers to form an opinion about the competence of the service agent i.e., the chatbot in this case. These queries contribute to tasks, which are activities involved in completing the job. The quick resolution of queries or guidance about the next steps also leads to satisfaction and further intention to use and engagement with the technology.

In their research, Huang and Rust (2021) have pointed out that tasks that require lower intelligence should be replaced first. All tasks will not be done by AI and provided a basis for segregating the tasks. But all tasks are not the same, some can be quickly resolved as they are not complex, could be mechanical and thus easy to resolve with the help of a chatbot. Complex tasks, on the other hand, could comprise many tasks, interdependent on other tasks, people or require more information. Thus, type of tasks could be factors that determine whether a consumer will select a chatbot for service. Whether the customer would like to interact with the chatbot when the query /task is complex is not yet been researched (Dwivedi et al., 2021; Larivière et al., 2017). Specifically in the context of chatbots what are the tasks consumers would like to use a chatbot has not yet been researched (Dwivedi et al., 2021; Larivière et al., 2017). Shahab et al. (2021) have mentioned mere exposure effect and other consumer behaviour theories have not been studied in the context of modern technology and marketing.

The study proposes that the nature of the query based on task complexity is an important motivation that influences the choice of service mode, in case of this study it is a chatbot or phone executive. To understand the impact of task complexity on the preference to use a chatbot the study uses task technology fit.

The first research question is to understand what kind of queries consumers are likely to prefer chatbots over traditional methods like telephonic conversations. Although there have been many research studies on chatbots in the last few years, there is hardly any study that looks into the preference or motivation of choosing a chatbot, especially when based on the nature of consumer queries. To answer this research question the consumer queries are categorized using two factors, time pressure and task complexity, in the theoretical framework and test for which type of queries consumers tend to choose chatbots.

When a chatbot is able to solve the query with or without the help of a human agent may lead to a positive experience and consumers may feel that chatbots are suitable for query resolutions. Whereas, the inability of chatbots to solve the queries and redirect the consumers to another platform may lead to a negative experience and drive consumers to use another channel. The study examines how different exposures and task characteristics, in the context of customer service influence consumer's choice to choose a chatbot.
Therefore, the second research question examines influence of positive and negative exposures, and decision point theory on consumer's perception of chatbot's ability to resolve a query.

To answer these research questions, the study draws upon task technology fit theory (Goodhue & Thompson, 1995), mere exposure effect (Zajonc, 1968) and decision point theory (Cheema & Soman, 2008). Task technology fit theory helps us understand the choice of chatbot under various situations. Mere exposure effect helps to assume that exposures could influence the consumer's choice of chatbot to solve the query. Decision point theory helps us to understand customer's perception of chatbots in various dialogues and its future adoption.
The hypotheses were examined through two experiments testing the use with four scenarios in each study in a 2 (Task complexity: complex vs. non-complex) × 2 (Time Pressure: urgent vs. non-urgent) factorial experimental design. The first study has used banking context. The second study uses different industries to increase the generalizability of the findings. These scenarios are chosen through a detailed pre-testing procedure explained later in the study to correctly represent the four experimental manipulations. The consumer preferences are first captured to choose a chatbot or telephonic conversation in a pre-test. All the respondents are then exposed to chatbot interactions related to their respective scenarios. In the post-test, the

same consumer preferences are measured again after the exposure to chatbot interactions in addition to the perceptual measures.

2.2 THEORETICAL BACKGROUND AND CONCEPTUAL FRAMEWORK

2.2.1 Task Technology Fit Theory

The Task Technology Fit theory (Goodhue & Thompson, 1995), suggests that users are more likely to adopt a technology if it helps them complete their tasks efficiently. This theory has been supported by numerous studies, including Pagani (2006) who found that users are more likely to adopt technology that helps them perform their tasks effectively. The fit between technology and task is an important factor in determining user's intention to use the technology and could also influence user satisfaction (Lin, 2012). Furthermore, Cheng et al. (2021) conducted a study that revealed how task complexity as a task characteristic can impact the relationship between chatbot attributes like empathy and friendliness, and the user's intention to use the technology. Previous research in task technology fit has indicated that task complexity is an important factor and can impact the effectiveness of service technologies (Speier & Morris, 2003; Xu et al., 2014; Zigurs & Buckland, 1998).

With respect to current study query could be considered as a task that consumers often get in touch with the company for various requirements. Consumer queries could be inquiries relating to orders (Moore & Moore, 2004), clarifications about the products (S. Singh et al., 2018) or complaints about the product (Ang & Buttle, 2012; Galitsky et al., 2009). These queries could be varying in their complexity (Xu et al., 2020) and urgency. Chatbots are usually used to answer standard and routine queries (J. Singh et al., 2019) such tasks or queries could be classified as non-complex. Therefore, for non-complex queries consumers may feel the chatbot technology is a good fit because the chatbot is able to provide answer quickly. However, when the queries are complex, chatbots may not be able to solve it, under such circumstance chatbots may redirect the consumer to another channel. When the chatbot is unable to provide an answer and redirects the consumer to another channel, consumers may feel that the technology is not suitable for such queries or tasks and may prefer to interact with a direct channel such as phone call. Therefore, the study looks into the nature of queries based on task characteristic such as complexity and time pressure.

2.2.2 Task Complexity and consumer queries

To understand the role of complexity in the consumer query as a task characteristic, the study takes cues from task complexity literature (e.g. Xu et al., 2020). According to Wood (1986), task complexity is described as the amount of relevant information required for the performance of a task. It refers to multiple actions, that could include many levels of information or instructions to complete the task as against a simple task that may be completed by a single transaction (Cheng et al., 2021; Gong & Choi, 2016). It requires more time and effort to perform the task in case of high complexity (Xu et al., 2020). When a query has multiple acts or multiple information, this increases task complexity and is likely to increase the cognitive load for the consumer (Speier & Morris, 2003).

As mentioned chatbots currently are handling only non-complex queries, for a complex query, the consumer may not get a direct response from the chatbot. In fact, chatbots may direct the consumer to human agents. In such cases consumer may feel that interacting with chatbots and then getting redirected maybe more time consuming and therefore prefer a direct channel, e.g. telephonic conversation (Xu et al., 2020). Mozafari et al. (2022) argued that using a chatbot for customer service will be situational and depend on the complexity of the task consumer would like to perform. For complex tasks, consumers may also be concerned with the chatbot's ability to solve problems and thus may not prefer to use a chatbot (Cheng et al., 2021). On the other hand, when tasks are not complex and routine, consumers may prefer to interact with chatbots (Huang & Rust, 2018). Thus, the study proposes that for non-complex queries or tasks consumers may be able to interact with chatbots and solve their queries and therefore will find the chatbots suitable for such tasks.

H_1: Consumers are more likely to choose chatbots for non-complex queries than complex queries.

Task under time pressure:

Time pressure refers to the perceived limitation of time available to process information or decision making (Suri & Monroe, 2003). It is the gap between the time available and the time required to make a decision or complete a task (Peng et al., 2019; Rastegary & Landy, 1993; Spears, 2001; Van Steenburg & Naderi, 2020). Previous literature suggests that consumers tend to hasten the information examining process under time pressure (Ben Zur & Breznitz,

1981). They also tend to avoid negative choices (Huber & Kunz, 2007) and focus only on important attributes for their choices (Ben Zur & Breznitz, 1981; Svenson & Edland, 1993; Wright, 1974). Time pressure affects consumers' decision making and how they examine information (Young et al., 2012). In order to shorten the time available, consumers use inferences (Suri & Monroe, 2003) and heuristics to make decisions (Huaman-Ramirez & Merunka, 2017). When consumers feel time pressure, they are likely to choose a high-quality brand over a low quality (Nowlis, 1995). Probably, consumers wanted to take the lesser risk, so they chose the known brand when they were time-pressed. When consumers experience time pressure, they are likely to choose options that they think will simplify the process (e.g. Dhar & Nowlis, 1999). In queries with chatbots, time pressure could influence consumers' choice as they may prefer to use previously used traditional, tried and tested methods like the telephone. Choosing an existing method is likely to simplify the selection process (Dhar & Nowlis, 1999). Dabholkar et al. (2002) have studied moderating effects of time pressure, as a situational factor that influences intention to use technology based self services. In the context of this study, it is likely that queries under time pressure may prompt consumers to choose a direct medium such as speaking to an executive. Hence, the following hypothesis is proposed.

H_2: Consumers are more likely to choose chatbots for non-urgent queries than urgent queries.

2.2.3 Impact of positive and negative exposure on the choice of chatbot or a direct channel for customer service

Chatbots are present on the websites or mobile apps as a live chat agent to answer consumer queries. Consumers are exposed to chatbots while interacting with these websites or apps. Previous research on mere exposure effect indicates that the positive and neutral exposures to an object could lead to familiarity and further preference for the object. Exposure to chatbots may lead to preference to use a chatbot. Roy & Naidoo et al., (2021) in their experiment found that exposure to warm conversations enhanced consumer's purchase intentions. Mere exposure effect explains the tendency of individuals to develop a preference for something simply by being exposed to it repeatedly over time (Janiszewski, 1993; Zajonc, 1968). In other words, people tend to like things more when they are exposed to them more frequently.

This familiarity or recognition enhances the likelihood of preference for the object in future (Stafford & Grimes, 2012). Previously mere exposure effect has been used to study the link between the effects of exposure to brand images and attitude towards the brand (Lowry et al., 2008), exposure to web ads and favourable attitude towards the brand (Yoo, 2008). Frequent exposures to smartphone could lead to use of smartphones addictively (Montag et al., 2019). The meta-analysis of 208 experiments conducted by Bornstein (1989) found that the mere-exposure effect is most potent when unfamiliar stimuli are presented briefly. Thus, mere exposure effect is a robust phenomenon and often used to understand if exposures influence choices.

Chatbots in customer service can answer queries independently, leading to a positive exposure. However, if chatbots are unable to solve a problem, they can either hand over the query to a human on the same platform or redirect the consumer to another channel, such as a phone call. Under conditions where chatbots are able to solve the query independently or with human help, consumers will perceive chatbots as a good task technology fit. But in cases where chatbots are unable to solve the query and redirect consumers to another channel, consumers may perceive chatbots as unsuitable or poor task technology fit for such queries. This negative reaction could be explained with the help of the reverse mere exposure effect. Although familiarity could lead to preferences initially negative attitudes could strengthen negative affective reactions due to reverse mere exposure effect (Crisp et al., 2009; Giroux et al., 2023). Therefore, consumers are likely to perceive a chatbot suitable or good fit of task and technology for query resolution when chatbots are able to solve the query either independently or in tandem with a human agent. However, in cases where the chatbots are unable to solve the query, consumers are likely to find the chatbots as unsuitable or poor fit for the query resolution

2.2.2 Decision points theory

The decision points theory was developed by Soman, Xu & Cheema (2010). This theory emerged from various research papers (Soman, Dilip; Cheema, Amar & Chan, 2012; Soman et al., 2010; Soman & Cheema, 2011). These papers studied how increasing the number of decision points in a given task can lead to friction and lesser use or consumption (Soman, Dilip; Cheema, Amar & Chan, 2012). A decision point is defined "as any intervention that is designed to get an individual to pause and think about the current state they are engaged in".

By creating an interruption in the consumption consumers are forced to reflect on their current stage and thus this creates a decision point (Soman & Cheema, 2011). Decision points pause the automatic stage and force a consumer into a deliberative mode to think, read, and reflect (Farghly et al., 2022).

In the current study, when chatbots need human help for certain queries, providing human help in the same window does not increase their decision point as consumers are provided help in the same window. However, when the chatbot asks the consumer to connect on the phone by providing the customer care number, it increases the decision point significantly. Some of the additional decision points could involve closing the chat window, clicking on the link, and calling the customer executive. This may require the customer to explain the entire query from scratch. In some cases, the process could involve further additional steps. The increase in decision points is likely to lead to negative exposure and consumers are less likely to choose chatbots for future use. Based on the above arguments, the following hypotheses are proposed:

H_3: Consumers' preference to choose chatbots in the future is likely to decrease as the decision points increase.

2.2.4 Outcome Variables:

Perception of competence of chatbots:

When dealing with a chatbot the autonomous conversation provides customer with the solution. Service interaction involve some form of communication and based on these customers infer about the perception of the service employee such as competence. positive: When two people meet for the first time, they immediately form initial ideas from each other. Perception of competence influences further relations with customers (Chung et al., 2018). In case of chatbots when they able to complete a task with accurate guidance customers consider them as competence. The perception of competence is important, as it establishes trust in the customer to conduct a future transaction through the chatbot. In case of AI augmented dialogue, AI assisting human, a quick response that also includes correct guidance and handing over the dialogue to an executive and leads to positive perception of chatbot's competence in completing a transaction. In the study by Longoni et al. (2020) AI

recommenders were found to be competent in case of utilitarian goal and human recommenders were found to be more competent in case of hedonic goals. In line with this research, it is proposed that when complexity is triggered due to the expected time and effort consumer's perception of chatbot being able to complete the transaction is low. However, under non complex tasks a chatbot is able to execute the query independently and thus the perception of competence is higher. Hence,

H_4: Consumers are likely to have a higher perception of competence of the chatbot in case non-complex and non urgent queries than complex queries and urgent queries.

Satisfaction:

Consumer satisfaction is heightened when consumers are satisfied with the choices made at the time of purchase (Chung et al., 2018). Previous studies have found satisfaction is one of the most important factor that has positive relationship with brand loyalty (Sureshchandar et al., 2002). When it is used in context of devices or technology it facilitates adoption and continued usage and is linked to repurchase intent (Mittal & Kamakura, 2001). For example, if the mobile is able to provide satisfaction due to easy accessibility, user control, time convenience it leads to adoption and continued usage of mobile technology (Kleijnen et al., 2007). Performing accurately (i.e. "doing its job") is an important source of satisfaction, particularly for emerging technologies that may evoke users' suspicion (Meuter et al., 2000). In case of chatbots perceived accuracy in communication, when customers feel that their questions are answered accurately and reduces uncertainty it increases satisfaction (Chung et al., 2018). In many cases it is seen that chatbot design support a handover of conversation to an executive after a few conversations or question answers. When chabots fail to respond with an accurate answer to a customer it can lead to dissatisfaction (Diederich et al., 2021). This is more likely to happen in case of complex queries wherein tailored responses are difficult in case of an automated dialogue. Customer query resolution, instant and independent ability to solve a query can lead to satisfaction in using the chatbot as a service mode. However, in case of non-complex query the chatbot is able to provide a quick solution as compared to a complex query where the conversation seems to be longer with multiple question. Thus, when consumers are able to get quick resolution, the satisfaction is higher. Nevertheless, the likelihood of quick resolution is higher in case of non-complex queries as compared to complex once. Hence, the following hypothesis is proposed,

H_5: Consumers are likely to have higher satisfaction for their query resolution with chatbots in case of non-complex and non urgent (no time pressure) queries as compared to complex queries and urgent (time pressure)..

Intention to use

Based on TAM factors such as ease of use and usefulness of technology determine intention to use (Davis, 1989). However, these two factors are not enough to explain intention to use and other context-based factors also influence user's intention to use the technology. Later researchers have extended TAM by adding other variables such as perceived playfulness (Moon & Kim, 2001), compatibility (L. da Chen et al., 2002), perceived user resources (Mathieson et al., 2001), trust (Gefen, 2002), and perceived credibility (Wang et al., 2003). In case of chatbots quick query resolution leads to an intention to use the technology for the future.

H_6: The intention to use the chatbot in future is likely to be more for non-complex and non urgent (no time pressure) queries as compared to complex queries and urgent (time pressure).

Engagement:

Engagement refers to the state of being involved, retained, occupied and intrinsically interested in something (Pagani & Mirabello, 2011). For a technology to be successful it is important that it is able to engage the user (O'Brien & Toms, 2008). Engagement with a chatbot is referred to the ability of the chatbot to converse with the customer and provide thoughtful responses (Holtgraves et al., 2007; Moriuchi et al., 2021). Natural flow of the conversation is an important factor in making the chatbot as engaging (Koufaris, 2002). Literature in technology engagement suggests that companies use technology to different themselves. Engagement with online medium is likely to increase the advertisement effectiveness placed in the medium (Malthouse & Calder, 2010). Thus engagement is an important outcome that influences attitude towards a company, and prompts companies to put efforts in seeking more than involvement (Moriuchi et al., 2021). When the chatbot is able to respond and maintain a flow of conversation with customers will be interested in the conversation and will find the chat engaging and useful.

Accordingly, it is proposed that engagement is an important outcome and when the customers are able to get solution to their problem the engagement is likely to be higher.

H_7: The engagement is likely to be higher in case of non complex and non urgent queries as compared to complex and urgent queries.

The above relationships are presented in the following proposed conceptual framework

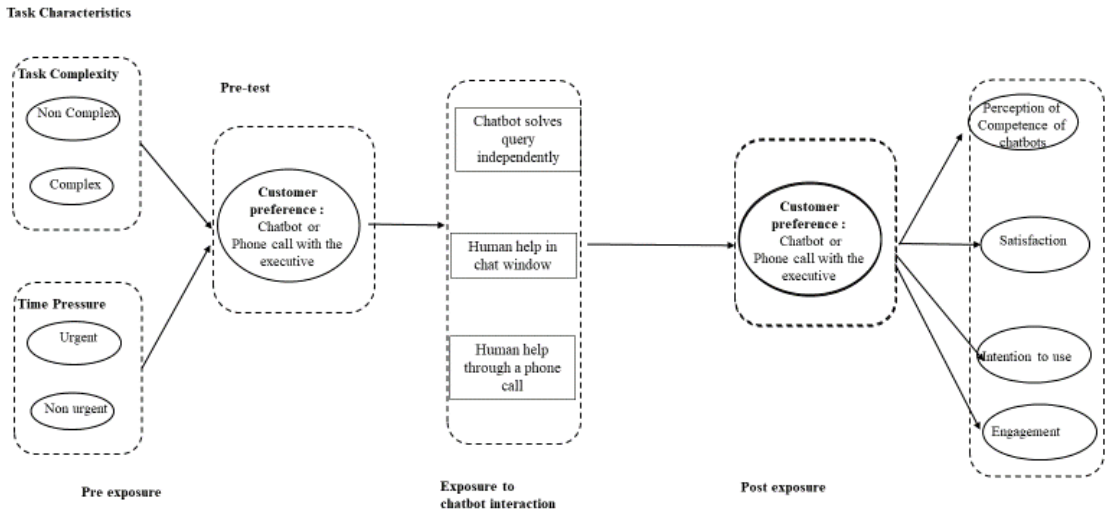


Figure 1

2.3 Research Methodology:

The hypotheses were tested through two studies. In Study 1, four scenarios were created based on the banking industry to investigate consumer preferences for customer service interactions with chatbots versus phone calls, depending on the complexity and urgency of the query. Many public and private sector banks have deployed chatbots to provide customer service, but currently, these chatbots redirect consumers to other platforms for complex or urgent queries. Taking cues from this, the scenarios were designed wherein the chatbots

solved non-complex and non-urgent queries but redirected consumers for complex and urgent queries.

In Study 2, scenarios from different industries were used for two reasons, firstly, to increase the generalizability of the study, and secondly, unlike the banking industry, ecommerce and food delivery companies are deploying chatbots to solve a wide range of queries either independently or with the help of human agents on the same platform. Thus, it allowed us to operationalize the scenario for query resolution by chatbot and human agents together. In order to uncover the true perception of consumer scenarios inspired by real-life situations were used, it was important to carefully select these scenarios through pre-testing to depict the real-life situations faced by consumers. Therefore, for both studies, scenarios were carefully selected through pre-testing to ensure their realism. A similar approach has been used for the experiments conducted by Longoni et al., (2020). Scenarios based study was designed to reduce effects of any confounding variables, similar studies are done previously using experiment based methodology (Chung et al., 2018; Longoni & Cian, 2020; Rzepka et al., 2021; Sands et al., 2020).

2.4 EXPERIMENT 1

Four distinct customer query scenarios were created : 2 (task complexity: complex vs. non-complex) x 2 (time pressure: urgent vs. non-urgent) for the banking industry. The scenarios were finalized in a pretesting where respondents rated their perceived urgency and complexity on a scale of 1 to 10. The final selected scenarios based on these ratings are presented in Appendix A. The complex scenarios have been adapted from Xu et al. (2020). Manipulation checks were conducted as done in Jiang et al., (2007b). The results from one-way between-groups analysis of variance confirmed that the manipulations were working and were significant for urgency F (3, 116) = 33.25, p = 0.00. The Post-hoc comparisons using the Tukey HSD test indicated that the high-urgency scenarios, scenario 4 (M= 9.3 SD = 1.6) and scenario 2 (M=7.6 SD = 2.3) were significantly different from the low-urgency scenario, scenario 1 (M= 4.3 SD = 1.76) and scenario 3 (M= 5.9 SD = 2.35). The results for complexity were also significant F (3, 116) = 38.59, p = 0.00, indicating the manipulations have worked. The Post-hoc comparisons using the Tukey HSD test indicated that the high complexity scenarios, scenario 4 (M=9 SD=1.7) and scenario 3 (M=7.3 SD=2.0), were

significantly different from the low complexity scenario, scenario 1 (M= 3.66 SD =1.98) and scenario 2 (M= 5.1 SD = 2.4).

Participants and procedure:

A total of 142 management (73.2% were male) students studying in a university in Mumbai participated in the study, with an average age of 24 years. The majority of the participants were MBA students from a university in Mumbai. The student sample was considered for this study as they are tech-savvy, motivated to use AI tools (Chopra, 2019), and often use online services (Makarem et al., 2009). Participants were from different cities in India but studying in Mumbai. They were randomly assigned to one of the four conditions and given a brief introduction about the study and a scenario to read. The scenarios, as stated earlier were designed to depict a condition that required customer service help. A google form was circulated and the participants were asked to choose between a chatbot and a phone call if they were in the scenario and needed assistance. The next section presented a chat dialogue wherein chatbot had extended help for a similar query. The sample chat dialogues used in this study are given in Appendix B. Post the chat dialogue exposure they were again asked to mark their choice between a chatbot and a phone call. Pre-test and post-test both responses along with demographic details were collected through google forms.

Pretesting:

The pre-test results showed that consumers preferred chatbots for non-complex and non-urgent queries, but when urgency was introduced, they preferred phone calls. After presenting the chat dialogues, it was found that consumers preferred chatbots when the query was not complex and the chatbot could solve it independently. However, as the urgency increased, consumers preferred phone calls as chatbots were only partially able to solve the query and directed consumers to a consumer care representative.

Dependent variables:

The dependent variable for this study was a binary choice between a chatbot and a phone call. The mere exposure effect was measured with the use of pre-test and post-test data.

Results

Respondents were asked to choose between a chatbot and a phone call to solve a query. The results from crosstab analysis for both pre-exposure and post exposure show that in a non complex and a non urgent scenario greater number of consumers (40.7%) preferred to interact with a chatbot than a phone call. But when the complexity increased a greater number of consumers preferred phone call over a chatbot for query resolution, 77.5% for non-complex and urgent 82.5% in case of complex and non urgent and 89.1% for complex and urgent. Similar results were seen urgency scenarios. The crosstabs results were statistically significant χ_2= 9.446 p=0.02. and support hypotheses H1, H2. The results are presented in the Table I below:

Table 1

Pre exposure crosstab results

Scenario	Phone	Chatbot	
Non-complex and non urgent	16 (59.3%)	11 (40.7%)	27 (100%)
Non-complex and urgent	31 (77.5%)	9 (22.5%)	40 (100%)
Complex	24 (82.8%)	5 (17.2%)	29 (100%)
Complex and urgent	41 (89.1%)	5 (10.9%)	46 (100%)
	112 (78.9%)	30 (21.1%)	142 (100%)

Post exposure results:

Scenario	Phone	Chatbot	
Non complex	4 (14.8%)	23 (85.2%)	27
Non-complex and urgent	29 (72.5%)	11 (27.5%)	40

Complex and non urgent	23 (79.3%)	6 (20.7%)	29
Complex and urgent	44 (95.7%)	2 (4.3%)	46
	100 (70.4%)	42 (29.6%)	142

Post exposure results suggest that in the scenarios where the chatbot solved the query i.e., a non complex and non urgent situation, which was a positive exposure, consumers perceived chatbots to be suitable for such tasks. In this experiment after exposure to a chat interaction 85.2% consumers have chosen a chatbot as compared to 40.7% consumer in pre-exposure condition for a non complex and non urgent situation. The chatbot in the chat interaction in this scenario is shown to resolve the query. Therefore, in case of positive exposure consumer are more likely to switch to chatbot than a phone call. In the remaining three scenarios the queries were not solved and the consumers were redirected to phone call. These were negative exposure the consumers preferred a traditional method of customer service, such as telephone call over chatbot as shown in the results in Table 1 post exposure section.

Further, the Mcnemar tests given in Table II supports hypotheses H1.

Table 2 Mcnemar results study 1

Study 1	Post exposure		P-value
Pre-Exposure	Phone	Chatbot	
Non-complex and non urgent (N-27)			$p<0.05$
Prefer to use phone	4	12	
Prefer to use chatbot	0	11	
Non-complex and urgent (N=40)			$p>0.05$
Prefer to use phone	24	7	
Prefer to use chatbot	5	4	
Complex and non urgent (N=29)			$p>0.05$
Prefer to use phone	19	5	
Prefer to use chatbot	4	1	

Complex and Urgent (N=46)			p>0.05
Prefer to use phone	40	1	
Prefer to use chatbot	4	1	

Mcnemar results confirm that the positive exposure had a significant influence in conversion of choice from phone to chatbot, these results support H3a. However, the negative exposure conversions were not significant.

Experiment 2

As indicated in the first section, study 2 was an extension of study 1 model to include ecommerce context along with banking context. The communication with a chatbot is likely to have an significant effect on satisfaction, intention to use (Mero, 2018) and perception of competence (Longoni & Cian, 2020) hence these were captured as dependent variables for this study.

Method

Pretesting: The scenarios presented in Appendix B were shortlisted amongst many scenarios from different industries faced by different consumers and when they interacted with the company using either chatbots or using the telephone. The respondents were asked to rate these scenarios on urgency and complexity from 1 to 10. Based on the scores received from the respondents, the four scenarios were shortlisted. The shortlisted scenarios are presented in Appendix B.

Scenarios and Stimuli used:

Chat interactions: Once the scenarios were finalized, actual interaction were conducted with the real chatbots of the different companies operating in the respective industry to get the resolution these queries. For complex queries, the real-world chatbots were not able to solve the queries independently and took human help. However, they were able to solve it independently and accurately for non-complex queries. The urgency of the queries did not

play any role in the chatbot's ability to solve the queries independently. Based on these real interactions with chatbots, the sample interaction is prepared for each scenario. The sample interaction for all four scenarios is shown in Appendix D.

Participants and procedure:

Participants and procedure: A total of 208 respondents participated in the study, and 62.5% of them were males. The mean age of the participants was 29 years. Each scenario was presented through an online google form. The forms were randomly sent to the list of students participating in the study. After going through the scenario, they were asked to choose between a chatbot and a phone call with an executive to get this query resolved. This question measured the pre-test response of participants. Respondents were then told that the stimuli were based on similar previous interactions with the company's chatbot based on their scenario. In the next section, participants were exposed to the sample chatbot interactions related to their respective queries. They were asked to make the same choice between chatbot and phone call, which measured the post-test response. Next, their responses to the perceptual dependent measures were captured.

The demographic characteristics of the respondents for Experiment 2 is given in table 3 below:

Table 3

Demographic Factors		**Study1**	**Study 2**	**Study 3**	**Study 4**	**Total**
Gender	Male	26	37	34	33	130
	Female	26	19	19	14	78
Total		52	56	53	47	208
Age Group	15-25yrs	22	33	24	20	99
	26-35	15	21	19	17	72
	36-45	4	0	6	4	14
	46-55	9	0	2	4	15
	55 and above	2	2	2	2	8

Previous Chatbot experience	No	15	7	14	9	45
	Yes	37	49	39	38	163

Dependent variables:

Similar to study 1 the first dependent variable is a binary choice between a chatbot and a phone call. In this study additionally the other dependent variables such as satisfaction and intention to use were examined. The measures for the additional dependent variables were adapted from previous studies. Satisfaction was captured using the question, "How satisfied are you with the chatbot's interaction" with endpoints 1 (not at all satisfied) to 10 (very satisfied). Intention to use was captured by, "How likely are you to use a chatbot for similar queries in future" with endpoints 1 (very unlikely) to 10 (very likely). Satisfaction and intention to use were adapted from Belanche et al. (2012). Perception of competence adapted from Longoni & Cian (2020) was captured using the question "Was the chatbot competent to solve the query entirely?" with endpoints 1(not at all competent) to 10 (very competent).

Pre-test and Post results: The pre-exposure results of experiment 2 found that the complexity and urgency of the query affect the choice of chatbots. For non-complex queries, 67.3% of the respondents chose chatbots when the query was not urgent. When the query was urgent, even for the non-complex query, the choice of chatbot decreased to 30.4%. For complex queries, the choice for chatbot was much less as compared to the non-complex and non-urgent query. It was 38.3% for complex and urgent and 35.8% for complex and non-urgent query. The results were statistically significant (χ^2=17.735; p=0.000). These findings provide support to hypotheses H_1 and H_2. Like Experiment 1, all the participants were then exposed to chatbot-interactions where all the queries were solved in the chat window itself. The post-exposure results found that 92.3% of respondents chose chatbots for non-complex and non-urgent query. As predicted, the reduction in decision points led more consumers to adopt chatbots for future use as compared to experiment 1. The results found chatbot adoption increased to 76.8% as compared to 30.4% in pre-exposure for non-complex and urgent query. For complex and non-urgent query, chatbot adoption increased from 35.8% to 62.3% after the

exposure. Finally, for complex and urgent query also, chatbot adoption increased from 38.3% to 70.2%. The post-exposure results for all the four queries were statistically significant (χ^2=13.714; p= 0.03). To further check the robustness of our results, we conducted the McNeymar test as done in experiment 1 to compare pre and post-exposure results. Contrary to the results of experiment 1, the results of the McNeymar test are significant ($p<0.05$) for all four queries. These findings provide support to hypothesis H_3.

However, after exposure to a positive chat interaction consumers preferences changed and a greater number of consumers preferred chatbot over a phone call. For a non complex and a non urgent situation majority (92.3%) of consumers preferred a chatbot. After exposure to the chat interaction, the shift in consumers from phone call to chatbot was higher in the non-complex and non urgent scenario than other three conditions. The crosstab results are for pre and post exposure given in the Table IV below for all four scenarios.

These results are significant for both pre-test (Pearson's $\chi^2 = 17.735$, $p = 0.00$) and post-test (Pearson's $\chi^2 = 13.714$, $p = 0.03$)

Table IV Crosstab results - Pre exposure

Scenario	Phone	Chatbot	
Non-complex and non urgent	17 (32.7%)	35 (67.3%)	52 (100%)
Non-complex and urgent	39 (69.6%)	17 (30.4%)	56 (100%)
Complex and non urgent	34 (64.2%)	19 (35.8%)	53 (100%)
Complex and urgent	29 (61.7%)	18 (38.3%)	47 (100%)
	119 (78.9%)	89 (21.1%)	142 (100%)

Post exposure results:

Scenario	Phone	Chatbot	

Non complex and non urgent	4 (7.7%)	48 (92.3%)	52
Non complex and urgent	13 (23.2%)	43 (76.8%)	40
Complex and non urgent	20 (37.7%)	33 (62.3%)	53
Complex and urgent	14 (29.8%)	33 (70.2%)	47
	51 (24.5%)	157 (75.5%)	208

The Mcnemar results show that higher number of consumers shifted from phone call to chatbot under positive exposure supporting H3a and H3b. Study 2 was designed to include only positive exposure, wherein the chatbot solved queries independently in scenario 1 and other three scenarios handed over the query to a human agent. The results are significant for all the three scenarios and given in Table V

Table V Mcnemar results for study 2

	Post exposure		P-value
Pre-Exposure	Phone	Chatbot	
Scenario 1; Bank (N-52)			0.00
Prefer to use phone	4	13	
Prefer to use chatbot	0	35	
Scenario 2 ecommerce (N=53)			0.00
Prefer to use phone	18	16	
Prefer to use chatbot	2	17	
Scenario 3 food delivery (N=56)			0.01
Prefer to use phone	9	30	
Prefer to use chatbot	4	13	
Scenario 4 ecommerce (N=47)			0.00

Prefer to use phone	13	16	
Prefer to use chatbot	1	17	

Outcome Variables*:* As predicted, the results found that satisfaction for non-complex queries (Mean=8.16) is significantly higher than for complex queries (Mean=7.53, $p<0.05$). The main effect of time pressure and the interaction effect of time pressure and task complexity were statistically insignificant. The intention of future use also showed similar results like satisfaction. Intention to use for non-complex queries (Mean=8.04) was significantly higher than complex queries (Mean=7.44, $p<0.05$). For the intention to use also, both the main effect of time pressure and interaction effect of time pressure and task complexity were statically insignificant. These results provide support for hypotheses H_{5b} and $H_{5c.}$ The results for the perception of competence found that the main effect of both time pressure and task complexity were insignificant. However, the interaction effect of both task complexity and time pressure were significant, with a maximum score for non-complex and non-urgent queries (Mean=8.35, $p<0.05$). Results do not provide support for hypothesis $H_{5a.}$ Consumers perceived the chatbot to be most competent in case of very easy queries and when they were not urgent.

Chapter 3

Essay II: Customer Interaction with AI based Voice Agents (VAs)

3 Introduction:

VAs, powered by AI have been used by consumers to help in their day-to-day tasks such as playing music, setting up reminders, and alarms, and reading stories aloud to consumers. AIVAs are defined as voice-based conversational agents, that can perform the task through voice command and possess the ability to self-learn and therefore can assist customers in their decision making (Dellaert et al., 2020; Lim et al., 2022; Mari, 2019). VAs with voice interfaces like Apple Siri 2011, Cortana 2013, Alexa 2014, and Google Assistant 2016, have been around for a few years and are given human-like voices and language to communicate with the users (Hoy, 2018). Advances in AI, VAs are making their foray into assisting customers in a purchase transaction, allowing quick information search, recommending products through an algorithm, and making life for a consumer easier by saving time and effort e.g., Alibaba's Tall Genie (Sun et al., 2019). Convenience-based features like these have contributed to changing user habits when it comes to searching for products/ information and making purchase decisions (Munz & Morwitz, 2019). A growing number of features and platforms especially when coupled with smartphones has seen a surge in digital assistant and are becoming a vital part of the daily life of consumers (Guzman, 2019; Hearst, 2011).

Currently, Amazon Alexa is the AI technology that gives communication and understanding ability to the speakers like Echo, Echo Show 8, Echo Studio. Besides other 'skills', Alexa is also capable of conducting a product search and executing a purchase transaction. This skill has been recently added to Alexa in the Indian subcontinent (*Alexa for Shopping in India*, 2020). Other voice-controlled smart devices such as Google home, Apple pod are available and perform many tasks for the users. Siri is the VA available with Apple iPhone and Hey Google, for android phones. By giving an interactive voice to a device, gadget etc., tasks are performed by merely a voice command that also enables a user to multitask (Mclean & Osei-frimpong, 2019; Nass Clifford, 2005). Searching, and purchasing through the smart speakers that are enabled with AI adds another touchpoint in the consumer's purchase journey (Smith, 2020).

Purchasing by giving a voice instruction or command in the human world is not new. Voice is often used in daily life and human to human transactions for shopping e.g., giving order in a restaurant for a dish or ordering items on the phone. Therefore, it is the most natural way of communication (Nass Clifford, 2005). When human attributes are assigned to computers such as speaking skills or voice technology people involuntarily or unknowingly attribute social rules and expectations mindlessly to computers (Nass & Moon, 2000). AI-based VAs are far more advanced than a computer and designed to have more human-like features this in turn influences psychological connections, as in the case of robots. Due to such social cues' consumers tend to accept recommendations made by VAs (Rhee & Choi, 2020).

Voice technology extends beyond smart speakers and is embedded in many devices cars, home appliances, and mobile apps. When the VAs are used to conduct shopping, search or purchase this is known as voice commerce (Mari, 2019). Devices enabled with VA's or voice technology can be used from a certain distance for example Amazon Echo speakers with Alexa can be activated with a "wake word" even without touching as long as the machine is connected. Speaking to a device to perform a task offers benefits such as interactive and quick reply, simple and easy language to operate a machine that otherwise would require sitting down and typing a command and allows multitasking for the user (McLean et al., 2021). This helps increase personalization and boost customer experience. Many industries and companies are embracing voice technology e.g., Domino's voice activates ordering (Samuely, 2014). In the area of shopping VAs are offering a new direct to customer channel (Mari, 2019).

There is growing optimism for use of VAs in voice commerce (Klaus & Zaichkowsky, 2020). A report by Juniper Research (2018) has predicted that VAs in use will triple to 8 Billion by 2024. The adoption of voice assistants in the smart home area is growing(Accenture, 2019). A report from PWC (2019) has mentioned an increase in voice technology in other felds such as ecommerce, smart devices, hotel service and other areas. Gartner in their report has predicted that voice technology is going to be the trend in human-machine interaction. Consumers would expect a voice interface on their devices. Apart from these industry reports, academic research is also gearing up to build more understanding in the area of AI and consumer behaviour (Davenport et al., 2019; van Doorn et al., 2017) as not much is known in the area of consumer behaviour and artificial intelligence. Growing users for VAs may indicate that they are competent to perform simple task. However, when it comes to shopping do customers perceive a VA to be competent under all conditions is unknown.

Furthermore, understanding user behaviour with voice technology has been marked as a research priority by MSI (2020). Moriuchi (2019) has suggested that an experimental study could help in understanding how customers interact with VAs for specific tasks and specific product categories.

Customers use VAs for accessing information (Moriuchi, 2019) and get product recommendations for their search (Rhee & Choi, 2020). Information search for products is highly influenced by product involvement. Only if the customers perceive the VAs to be competent will they delegate the task of search and purchase to a VA. Perception of competence is defined as extent to which a person feels confident in VAs ability to execute a task. Task of searching information for products can be split in two parts searching for the correct match of the product and displaying results. The search results from the VA are presented in auditory mode or in a visual mode depending on the device (Munz & Morwitz, 2019). Presentation mode affects the way customer processes information (Munz & Morwitz, 2019). For example, a visual mode is able to present detailed information but is time consuming in contrast to an auditory mode which can present only limited information but saves time and is quick due to the minimum steps involved (Munz & Morwitz, 2019). Besides customers have the choice of the traditional mode of typing and searching. i

Early research in the field of VAs has mainly looked into effects of voice presentation, ts benefits and social effects on the adoption of VAs (Lee et al., 2020; Poushneh, 2021). As listening is easier than reading, voice presentation can be efficient and reduce cognitive load, leading to satisfaction (Rzepka et al., 2021). However, the product type plays an important role (Tassiello et al., 2021). For example, it is easier to understand simple products through only voice presentation than complex products (Munz & Morwitz, 2019). Especially for high-involvement products, the information quality is more important than the source; therefore, a voice presentation by a VA is insufficient for consumers to decide (Rhee & Choi, 2020). VAs can present information in two different modes: voice mode, as presented by 'Alexa' or both voice and visual modes like 'Siri'. Newer versions of VAs, such as Alexa and Google Home, are equipped with screens enabling high-quality information through visuals that could include product images and descriptions.

However, the work on VAs has focussed mainly on voice presentation, and only a few studies have attempted to examine the role of multiple presentation formats. A few studies in this area include work by Flavián et al. (2023), who compared text-based presentation in word of mouth (WOM recommendation) versus voice recommendation given by VAs and

found that the voice recommendations had a significant influence on perceptions such as credibility and usefulness and further these perceptions play a vital role in the adoption of VAs. However, the type of product (search or experience goods) did not significantly affect perception and behavioural intentions. Rzepka et al. (2021) compared the presentation format (voice vs text) in customer service and found that friendliness and efficiency in the case of voice format had a significant and higher impact on customer satisfaction in the case of utilitarian tasks. Through an experiment, Pagani et al. (2019) found that adding voice to a channel could reduce engagement with the channel. Other studies have examined the suitability of voice shopping for high and low-involvement products and found that voice is suitable for low-involvement products (Rhee & Choi, 2020; Tassiello et al., 2021).

Despite the growing research in the context of presentation formats of VAs, the commonly used voice and visual modes have not been explored yet. Multiple presentation formats (voice only, touch in the case of smartphones, or visual in the case of screens) are likely to affect marketing outcomes such as attitude, perception intent, etc. (Pagani et al., 2019). In summary, the influence of presentation mode and product involvement on the usefulness of VAs has not been studied yet. Moreover, consumers are likely to use VAs for product search and purchase only when they trust VAs and find them useful (Lim et al., 2022). Previous studies have indicated that trust and usefulness in the context of recommendation agents played an important role in their adoption (Benbasat & Wang, 2005). Some business reports in the context of VAs have indicated that users still do not trust AI technologies to perform tasks for them (Martin, 2019; Olson & Kemery, 2019). Accordingly, the first research objective is to examine the influence of product involvement and presentation mode on the consumer's trust and usefulness of a VA.

Trust and usefulness influence the intention to use a VA (Jiang & Benbasat, 2007a); hence, the study looks at the second research objective to examine the influence of trust and usefulness on behavioural intentions, such as the intention to use a VA and purchase products using a VA.

The study uses an elaboration likelihood model to understand the preference for AI VAs for different product involvement. To explain the presentation modes, this study integrates the CASA framework for voice presentation and dual coding theory for voice and visual presentation. In this way, the study responds to the call that the elaboration likelihood model

should be extended to artificial intelligence tools (Shahab et al., 2021). An experimental study was conducted with six conditions (3 presentation formats x 2 product involvement) to study the research objectives.

3.1 THEORETICAL BACKGROUND AND HYPOTHESIS DEVELOPMENT

VAs are voice-based conversational agents that can perform tasks through voice commands (Dellaert et al., 2020; Lim et al., 2022; Mari, 2019). Consumers interact with VAs by giving a voice command. In a typical scenario, the consumer may give a command to the VAs by first using a wake word, for example, the name of the VA, such as “Alexa, can you search for long exercise notebook.” The VA would search and announce the search results in voice. This is like most transactions we conduct on the phone, except here, the recommendations given by the VA are based on consumer preferences (Rhee & Choi, 2020). This presentation format is referred to as “voice presentation.” When the VA is embedded in a device with a screen in case of a similar search, they will present in voice along with a visual (Pagani et al., 2019); and is referred to as the “voice and visual presentation.” Additionally, consumers can manually search for products by typing text and receiving results in text or visual mode on a website, which is called the “visual presentation” (Whang & Im, 2021).

Spoken words are processed differently than written text ((Schwede et al., 2022). While the written text can present detailed information, voice is natural and easier to understand (Berger et al., 2022). Therefore, each presentation format offers unique benefits and could help in understanding the product information when a consumer searches for a product using the voice mode, and they can listen to the options; it is faster, natural, and easy to comprehend (Mclean & Osei-Frimpong, 2019). While this could be time and effort-saving for some products, it could pose a difficulty for some complex products because consumers must process this information mentally (Munz & Morwitz, 2019). Whereas in the case of visual presentation on websites online, consumers must type and go through the search results by themselves while it gives detailed information along with product descriptions and images, it is time-consuming as consumers must sift through vast information. On the other hand, the voice and visual presentation format of a VA announces the results in auditory mode and displays images. Compared to "only voice mode", this presentation can give detailed information to consumers and supplement the limited information given by voice

presentation with visuals such as images and descriptions. Since a VA conducts this search, it is more aligned with the user's previous history, making the recommendations more appropriate.

In addition, previous research has found that the presentation format was moderated by the type of products (Flavián et al., 2023; Rzepka et al., 2021; Wien & Peluso, 2021). For high-involvement products, consumers deliberate longer and need more product details for decision-making compared to low-involvement products. Time and effort spent by consumers are highly guided by the product type (Klaus & Zaichkowsky, 2022). Therefore, it is argued that the personal relevance of the product may influence the presentation format. The theory used is the Elaboration Likelihood model to understand the preference to use AI VAs for different product involvement.

3.2 Elaboration Likelihood Model and Product Involvement

The elaboration likelihood model by Petty & Cacioppo (1986) explains that people follow a different method to evaluate (elaborate) the persuasive effect of communication or information to form an attitude toward a product. When consumers lack the motivation and ability to process a message, they depend on cues and follow a peripheral route for low product involvement. When personal relevance is high, they like to scrutinize detailed information and use the central route (Bhattacherjee & Sanford, 2006; Y. Chen et al., 2018). Product involvement is critical in determining the processing route (Zaichkowsky, 1985).

In the case AI agents researchers have found that customers like to use AI for routine and simple tasks (Huang & Rust, 2018; Rzepka et al., 2021; Xu et al., 2020). Klaus & Zaichkowsky et al. (2022) in their conceptual paper have proposed that VAs are more likely to be used for low-involvement products. Some researchers have found that in case of habitual, routine items such as groceries, food items, books consumers find the services of VAs extremely useful (Munz & Morwitz, 2019; R. Singh, 2022; Tassiello et al., 2021). Such items are low-involvement and the personal relevance for these products is low. Therefore, it suits the needs for consumers and they look for cues to make their purchase decisions. On the other hand, high-involvement items, consumers seek detailed information and evaluate various options due to their importance or personal relevance (Tassiello et al., 2021; Yang et al., 2006). Whereas in the case of low-involvement products, which are routine and mostly

inexpensive, consumers prefer to spend less time and effort in gathering information. The decision-making process differs significantly between high and low-involvement products (Puccinelli et al., 2009). When employing VAs for product searches, the process is simpler, and the suggestions offered to consumers are not only rapid but also aptly tailored to their needs (Klaus & Zaichkowsky, 2022). The only effort required is to give the voice command. VAs help the consumer save time and reduce the effort required to search for the product. The information exchange with VAs via the peripheral route can be explained with the help of the CASA (computers as social actors) framework.

3.3 CASA Framework and Peripheral Route

Voice is generally considered a peripheral cue and most likely affects behaviour when the involvement is low (Chebat et al., 2007; Gelinas-Chebat & Chebat, 1992). The voice presentation by VA uses words such as ‘top search results are' and 'the ratings for the product.’ Though low on information, they work as cues for the consumer to make decisions. These narratives are likely to satisfy the peripheral route (Munz & Morwitz, 2019). One explanation for choosing VA for a low-involvement product is that it is easier to process limited information. Another explanation for using VA voice presentation comes from the CASA framework. As the CASA framework explains, humans apply the same social rules to computers as they would to humans (Nass et al., 1994). Users latently apply social rules to computers even though they know they are interacting with a computer (Nass & Moon, 2000; Schroeder & Epley, 2016).

3.4 Dual Coding Theory and Central Route

The visual presentation gives detailed information with product images and features listed. The consumer can read the ratings and reviews given by other consumers. Dual coding theory explains the visual presentation as a central processing route. Dual coding theory states that there are two brain subsystems for interpreting and information processing: nonverbal and verbal systems (Clark & Paivio, 1991; Paivio, 1965). It involves sensorimotor and symbolic systems. Visual, auditory, haptic taste and smell are sensorimotor, while symbolic systems include information processing using verbal and non-verbal systems. The verbal subsystem uses language, and the non-verbal subsystem uses imagery (Jiang & Benbasat, 2007a).

For this study, the verbal stimuli would include an auditory announcement of information in a human-like voice by VAs (Jensen et al., 2015). The nonverbal subsystem would include the visual information displayed by a VA. According to the extant literature, the dual-coded system (voice and visual text and images) should perform better than the single-coded system (Clark & Paivio, 1991) (VA like Alexa is an example of a 'voice-only' presentation, Siri, and Cortana are examples of voice and visual presentation). The presentation format and product involvement are likely to influence the trust and usefulness of VAs.

3.5 CONCEPTUAL FRAMEWORK AND HYPOTHESES DEVELOPMENT

3.6 Influence of Presentation Format and Product Involvement on Trust and Usefulness

Consumers may activate the peripheral route when searching for low-involvement products as the personal relevance is low (McNeill & Stoltenberg, 1988; Rhee & Choi, 2020) and may prefer less time and cognitive effort on such purchases. Searching for products using VA and listening to options reduces consumer time and cognitive effort. Therefore, for a low-involvement product, consumers may prefer to choose the VA with only hearing the options through a voice medium. When consumers listen to product features and details through voice, they associate the experience with interacting with a human being (Munz & Morwitz, 2019). The human-like voice of a VA replicates a transaction in a brick-and-mortar store. The naturalness of the voice presentation makes consumers feel like they are interacting with a human, surpassing the need for a visual presentation and specific product details (Klaus & Zaichkowsky, 2022). Furthermore, when purchasing groceries, a routine and habitual purchase, consumers are likely to delegate the task to a VA due to the emotional tie they have formed with a VA (R. Singh, 2022). Consumers may find these cues and the voice announcements of a VA useful in making their decisions (Rhee & Choi, 2020).

Consumers tend to engage the central route when dealing with high-involvement products, as the personal relevance of these products is significant. According to McNeill and Stoltenberg (1988) this means that consumers favour a thorough and rational approach to evaluating information. Voice assistants (VAs) embedded in devices can deliver information both audibly and visually (Pagani et al., 2019). This combination of voice and visual elements may

be particularly beneficial for consumers who prefer the central route. It allows them to access detailed information and read at their own pace. In contrast, a voice-only option cannot provide the same level of detail. Therefore, under conditions of high involvement, consumers are likely to prefer a mode that combines both voice and visual presentations. Based on this reasoning, the following hypothesis is proposed.

$H_{1:}$ Consumers are likely to prefer i) voice presentation for a low-involvement product and ii) voice and visual presentation for a high-involvement product.

3.7 Trust in the Competence and Integrity of a VA

VAs make personalized recommendations to consumers and can be helpful in product searches. However, consumers are more likely to accept VA recommendations only if they trust in VAs' ability to search and recommend products. Previous studies have highlighted the role of trust in human-computer interaction (Balakrishnan & Dwivedi, 2021; Lankton et al., 2015). In the case of online recommendation agents, trust played an important role in their successful adoption (Benbasat & Wang, 2005). The degree to which consumers feel they can rely on their VAs to complete tasks is called consumers' trust in voice assistants (Poushneh, 2021). When VAs deliver appealing, relevant, and trustworthy messages, consumers are likely to trust them. Trust in VAs is consumers' belief in a VA's competence and integrity. In the context of the current study, trust is likely to be influenced by presentation format and involvement.

Trust is a multidimensional concept and is defined as “an individual’s belief in an agent’s competence, benevolence, and integrity (Benbasat & Wang, 2005; Lankton et al., 2015). In this study, competence and integrity are considered as the dimensions of trust in the recommendation as benevolence is irrelevant. According to the definition, competence is the belief in a VA's ability, expertise, and skill to perform the task (product search). Regarding AI tools, prior research suggests a preference among consumers for non-complex and utilitarian tasks (Munz & Morwitz, 2019). Similarly, for VAs, consumers find recommendations credible for search goods compared to experience goods due to their human-like traits (Flavián et al., 2023). This suggests consumers may perceive VAs as competent for searching and recommending low-involvement products (Tassiello et al.,

2021). Therefore, it is hypothesize that trust in a VA is likely higher in a voice presentation for low-involvement products than for high-involvement products. Therefore, it is proposed,

H_{2a}: Trust in a VA is likely higher in a voice presentation for a low-involvement product than for a high-involvement product.

While integrating voice in a device can enhance trust, this effect reduces if perceived humanness is poor (Hu et al., 2021). For a high-involvement product due to the high personal relevance, consumers are more likely to depend on information quality or detailed information than the source or humanness (Rhee & Choi, 2020). In such cases, voice alone may not meet product information needs (Melzner et al., 2023). Similarly, relying solely on visuals can be time-consuming, making a voice-visual mode effective in addressing information requirements. Hence,

H_{2b}: Voice and visual presentations are likely to lead to a higher trust in a VA for a high product involvement compared to a voice-only or visual-only presentation.

3.8 Usefulness of a VA and Influence of Trust on Usefulness

Consumers evaluate technology mainly on its usefulness, and this serves as a reliable indicator of their future behavioural intentions (Bhattacherjee & Sanford, 2006; Y. Chen et al., 2018; Fernandes & Oliveira, 2021). Using VAs for shopping is useful when the technology assists consumers in gathering information and making purchase decisions (McLean et al., 2021). When VAs suggest recommendations, consumers are likely to navigate product searches easily, make informed purchase decisions, and find such information useful. However, the presentation format can affect the user's perception of usefulness. When the voice displays limited information for low-involvement products, consumers are inclined to accept recommendations due to the ease of processing information and the human-like qualities of the voice (Klaus & Zaichkowsky, 2022; Nass & Moon, 2000). Thus, it is proposed;

H_{3a}: Voice presentation by a VA is likely to lead to a higher perceived usefulness in a VA for a low product involvement than voice and visual or only visual presentation.

Conversely, for a high-involvement product, consumers may require detailed information, and voice mode is unable to fulfil the requirement of information quality (Melzner et al., 2023). Therefore, when human narrations are given along with visuals, consumers are more likely to find them useful because of the detailed information present in the message (Jiang & Benbasat, 2007a). For example, understanding the laptop product features through voice presentation can be difficult, but when this information is given along with product images and product descriptions, it could help consumers understand the product and read the information at their own pace. For such presentations, consumers would find recommendations given by VAs useful. While relying solely on visual mode might offer in-depth details, it could demand additional resources in terms of time and energy for product evaluation (Jiang & Benbasat, 2007a). Thus, the following hypothesis is proposed:

H_{3b}: Voice and visual presentation are likely to lead to higher perceived usefulness in a VA for a high product involvement than a voice-only or visual-only presentation.

Furthermore, when consumers trust VAs to recommend appropriate products, they find such information useful (Flavián et al., 2023). Benbasat et al. (2005) have found that trust in online recommendation agents highly influences usefulness. In the context of online health information, trust and usefulness were found to be important determinants of intention to use the e-service (Mou et al., 2017). Usefulness is important for consumers to adopt artificial intelligence tools such as VAs (Mariani et al., 2022). In line with the above argument, consumers are more likely to find VAs beneficial once they trust and believe that VAs are competent to search for the products. Therefore,

H_4: Trust in VA is likely to influence usefulness

3.9 Behavioural Intentions

Previous research on online shopping indicates that trust and usefulness are important determinants of behavioural intentions (Benbasat & Wang, 2005; Qiu & Benbasat, 2008). Behavioural intentions such as intention to use and purchase using a VA are important factors in understanding the consumer's future behavioural intentions (Flavián et al., 2023). In the

context of online recommendation agents, consumers' trust plays an important role in alleviating the uncertainty and complexity associated with online shopping. When consumers trust VAs to be competent in searching and recommending products, they are likely to adopt VAs under such circumstances (Benbasat & Wang, 2005). On the other hand, a lack of trust is anticipated to adversely affect behavioural intentions (Pitardi & Marriott, 2021). Consumers tend to delegate tasks where they believe VAs are competent to search on their behalf. These trusting beliefs are likely to influence behavioural intentions. Thus, it is hypothesized:

H_{5a}: Trust in VAs will have a positive influence on consumer's behavioural intention to use and intention to purchase using a VA.

Similarly, previous research suggests that usefulness is a strong predictor of behavioural intentions (Fernandes & Oliveira, 2021; Flavián et al., 2023). When consumers perceive that VAs can search and recommend products, this information helps them understand the product and make purchase decisions, and therefore, it is likely to influence behavioural intentions. Hence,

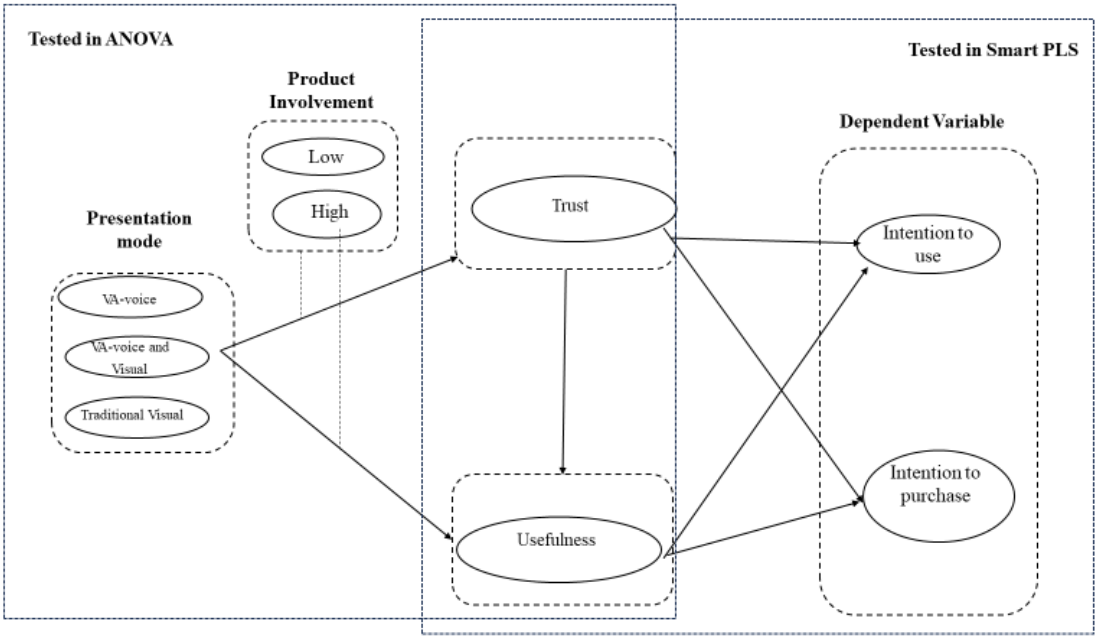
H_{5b}: Usefulness will have a positive influence on consumer's behavioural a) intention to use and b) intention to purchase using a VA.

Furthermore, following the work of Benbasat et al. (2005), the mediating role of usefulness is also examined in the framework.

H_6: Usefulness is likely to mediate the relationship between trust in the recommendation and behavioural intention, intention to use and intention to purchase using a VA.

Given below is the conceptual map (Figure 1), depicting the above relationships

Figure 2



3.10 OVERVIEW OF THE STUDIES

To test the hypotheses a 3 (voice only x voice and visual mode x visual only) x 2 (low x high product involvement) between subject design experiment was conducted. Scenario based study was designed to avoid any influence of confounding variables, previously studies have used similar methods using experiment based methodology (Chung et al., 2018; Flavián et al., 2023; Pagani et al., 2019; Rzepka et al., 2021). Accordingly, six scenarios were created and participants were randomly assigned to one of the conditions.

The audio and audio-visual stimuli were created using clipchamp app. The visual stimuli were prepared using canva.com. All the stimuli were based on real searches and products but a fictitious name / brand name was given. This was done to avoid any kind of bias, by the respondents to select the item. In each scenario the stimulus was presented to the respondents based on the condition they were assigned to. The message was played as per the condition the respondents were allotted to, so for a voice only condition the audio message by a VA was played, for voice and visual, a visual (text and images of the product) along with a VAs audio was played. Finally for the only visual, that is the traditional mode of searching the website only the visual was shown.

The visuals and the voice stimuli (products, name, description and ratings) were kept same for all the conditions for the purpose of the experiment.

3.11 Experiment Design and Method

A 3 (voice only x voice and visual mode x visual only) x 2 (low x high product involvement) between-subject design experiment was conducted to test the hypotheses. Six conditions were created, and participants were randomly assigned to one of the conditions. As suggested by previous researchers, a scenario-based study was designed to avoid any influence of confounding variables and a prescribed scientific experiment-based methodology was used (Chung et al., 2018; Flavián et al., 2023; Longoni & Cian, 2020; Rzepka et al., 2021).

3.12 Stimuli preparation

Manipulation check

The scenarios chosen were first circulated among 30 respondents to check if the necessary manipulations, product involvement, conditions were working. The scenarios were tested on level of involvement with 30 participants per condition. The manipulation results confirmed that the scenarios given were perceived as high and low involvement.

Results from the independent t-test confirmed that the manipulations were successful and were significant for low-involvement M_{30}=2.9 and high-involvement M_{30}=8.467, t= -16.244, p = 0.00.

Method

Product involvement was manipulated with the help of scenarios. A long exercise notebook was chosen for a low-involvement product, and a fiction book for high-involvement. Exercise notebooks are often used for writing among the students. Purchase decisions to buy the exercise books are frequent and objective-driven. Hence, it fits well into the category of low product involvement. Fiction books were chosen for high-involvement products, as readers buy fiction for pleasure and entertainment (Zunshine, 2012). Readers often look for reviews and advice regarding choosing a book (Ludwig et al., 2013).

The scenarios chosen were pretested with 30 respondents per condition to check if the necessary manipulations, product involvement, and conditions worked. The manipulation results confirmed that the scenarios given were perceived as high and low-involvement products. Results from the independent t-test confirmed that the manipulations were successful and were significant for low-involvement M_{30}=2.9 and high-involvement M_{30}=8.467, t= -16.244, p = 0.00.

After finalizing the scenarios, an investigation was conducted to explore the common search methods consumers use in case of three presentation formats available—specifically, 'voice only mode' with voice announcements and 'voice and visual mode'. Stimuli were crafted based on these investigations for online product searches and generated stimuli for each condition based on these investigations. For example, stimuli for both low-involvement and high-involvement products included three presentation formats: voice-only, voice and visual, and visual-only.

To control for the confounding variables, the same VA voice was used in 'voice only' and 'voice and visual' conditions. All the stimuli were derived from actual searches and products, but a fictitious name/brand name was given to avoid any respondent bias. In each scenario, the stimulus was presented to the respondents based on their assigned condition. The message was played as per the condition the respondents were allotted to, so for a voice-only condition, the audio message by a VA was played; for voice and visual a visual (text and images of the product) along with audio (same audio as used in voice-only condition) was played. Finally, only the visual was shown for the visual-only condition. The visuals and the voice stimuli (products, name, description, and ratings) were kept the same for all the conditions of the experiment. Appendix A gives all the scenarios, the respective messages, and the stimuli used in the study.

3.13 Measurement

Usefulness was captured using three items from Flavián et al. (2023). trust was measured as a second-order reflective construct, with competence (three items) and integrity (two items) as the dimensions and was adapted from Benbasat &Wang (2005). The dependent variables, intention to use and intention to purchase using a VA, were captured using three items each from Benbasat et al. (2005). All constructs were measured on a seven-point Likert scale.

3.14 Participants and Procedure

A total of 343 participants, with an average age of 27 years, voluntarily took part in the study. Among them, the majority of respondents fell within the Gen Z age cohort (20-30 years old), with 37% representing females. The selection of participants from Gen Z aligns with the study's focus, considering that individuals in this age group are often considered early adopters of technology and are motivated to engage with AI tools (Chopra, 2019). Respondents were given a brief introduction to the study followed by a scenario to read. After that, an online Google form was provided with a link to the respective stimuli (audio or voice, audio-visual or visual file) and a questionnaire. After engaging with the prompts, participants were presented with questions regarding their preferences, followed by the collection of demographic details.

3.15 Results

All the analysis were done using SPSS 21.0, and Smart PLS 4. The study has employed analysis of variance, ANOVA to test the statistical difference among the variables and to check for interaction between the categorical predictors. The influence of presentation format and involvement on trust and usefulness has been analysed with ANOVA. The influence of trust and usefulness on intention to use and intention to purchasing using a VA has been done in Smart PLS 4. Similar pattern of data analysis has been used in previous studies for e.g. Jiang et al. (2007b), Qiu & Benbasat (2008) and Balakrishnan & Dwivedi (2021).

Results on Trust and Usefulness

Univariate analysis was conducted on the two dependent variables usefulness and trust separately as it allows to check the main effect and interaction effect of the two categorical predictors, presentation format and product involvement. Presentation format had 3 groups. group 1 voice and visual, group 2 voice only and group 3 visual only. Product involvement consisted of 2 groups high and low.

The results indicated that main effect of format (F=3.852 p< 0.05) and involvement (F=7.912 p< 0.05) but involvement was insignificant on trust. The interaction effect of format x involvement on trust were significant (F=71.771 p< 0.05) given in Table 1.

Table 1

ANOVA results for Trust

Source	df	Mean square	F	Sig
Format	2	2.541	3.852	.022
Involvement	1	5.220	7.912	.005
Format x Involvement	2	47.349	71.771	.000

The results for usefulness indicated that main effect of format (F=3.094 p< 0.05) and involvement (F=4.913 p> 0.05) were significant. The interaction effect of format x involvement on usefulness were significant (F=9.450 p< 0.05) as given in Table 2. Thus, the main effects of format were significant on both trust and usefulness support H_{2a} and H_{2b}.

Table 2

Source	df	Mean square	F	Sig
Format	2	3.592	3.094	.047
Involvement	1	5.705	4.913	.027
Format x Involvement	2	11.407	9.450	.000

Figure 1

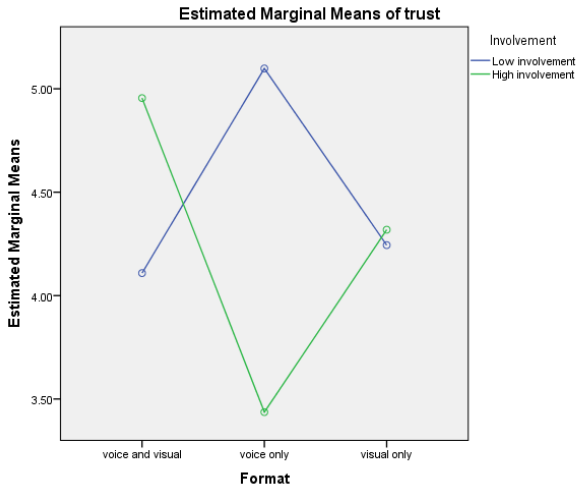
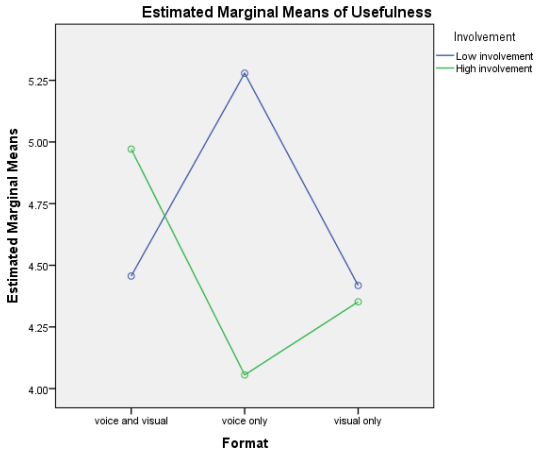


Figure 2



The significant interaction effect of format and involvement, in both trust (figure 1) and usefulness (figure 2) suggest that the effects of presentation format are moderated by product involvement such that usefulness and trust were higher for voice only format in low involvement condition thus supporting H_{3a} and $H_{3b.}$

The second half of the model as given in Figure 1 was tested using Smart PLS 4. To examine the internal consistency, factor loadings were checked. As presented in Table 3 all the constructs factor loadings exceeded 0.7 level except integrity was at 0.68 which is lower than 0.7 but in the acceptable range of .6 to .9 as suggested by Hair et al. (2019). Respondents filling a questionnaire having both independent and dependent variables in the same questionnaire could lead to common method bias or common method variance (CMV) (Podsakoff et al., 2003). To ensure that there is no CMV, a Harman Single Factor test in SPSS 24 was conducted. Results indicated that no single factor was responsible for the majority of the variance as it was lower than 50%.

Measurement validation:

Further checks were conducted on the reliability and validity of the model with Smart PLS 4. Bootstrapping process with subsamples was used (Chin, 1998).

Trust in recommendation was measured as a second-order reflective construct as done by Benbasat et al. (2005). The reason to do so was that the two beliefs viz., competence and integrity are highly correlated with each other.

The inner variance inflation factor values ranged from 1.0 to 1.406 and the outer VIF values were from 1.436 to 2.041. All the values were less than the recommended value of 5 hence there was no issue of multicollinearity (Dijkstra & Henseler, 2015).

Convergent validity was established using the average variance extracted and was greater than 0.5 for all constructs as suggested by Fornell & Larcker (1981). These values are given in the table 3 below.

Table 3

First Order Constructs	Factor Loading	Cronbach's α	Composite reliability (rho_a)	AVE
Usefulness		0.796	0.814	0.711
Useful1	0.875			
Useful2	0.889			
Useful3	0.76			
Intention to use		0.782	0.797	0.694
IntUse1	0.852			
IntUse2	0.805			
IntUse3	0.841			
Intention to purchase		0.778	0.797	0.691
IntPur1	0.842			
IntPur2	0.872			
IntPur3	0.776			
Competence				
Comp1	0.821	0.767	0.767	0.682
Comp2	0.85			
Comp3	0.806			
Integrity				
Int1	0.892	0.751	0.751	0.801
Int2	0.897			
Second order constructs				

Trust		0.701	0.711	0.769
Usefulness		0.796	0.81	0.711
Intention to use		0.782	0.786	0.689
Intention to purchase		0.778	0.796	0.691

Discriminant validity as given in Table 4 for first-order constructs and second-order constructs was established as the square roots of AVEs of each construct were larger than the corresponding correlations of interconstruct as suggested by Fornell & Larcker (1981).

Table 4

Discriminant validity lower order construct

	COMPETENCE	INTEGRITY	USEFUL	INTUSE	INTPUR
COMPETENCE	0.826				
INTEGRITY	0.52	0.895			
USEFUL	0.539	0.443	0.843		
INTUSE	0.485	0.385	0.531	0.833	
INTPUR	0.434	0.438	0.506	0.644	0.831

Discriminant validity higher order construct

	TRUST	USEFUL	INTUSE	INTPUR
TRUST	0.877			
USEFUL	0.563	0.835		
INTUSE	0.645	0.526	0.834	
INTPUR	0.468	0.508	0.645	0.831

Hypothesis testing

The results of hypothesis testing (a summary is given in Table 5), and relationship testing between independent and dependent variable were tested by the path coefficient (β) and t-statistics at 0.05 significance level ($p < 0.05$).

The R^2 results indicate the 35.6% variance explained by intention to use and 30.6% by intention to purchase. Trust had a positive effect on behavioural intentions viz., intention in use ($\beta = 0.339$, $p < 0.05$) and intention to purchase ($\beta = 0.267$, $p < 0.05$). This supports our $H_{2a.}$ Trust had a positive effect on usefulness ($\beta = 0.563$, $p < 0.05$), supporting H_4. Similarly, usefulness had a positive impact on behavioural intentions viz., intention in use ($\beta = 0.335$, $p < 0.05$) and intention to purchase ($\beta = 0.358$, $p < 0.05$) confirming H_{4a}

The mediating effects of usefulness on trust, intention to use ($\beta = 0.189$, $p < 0.05$) and intention to purchase ($\beta = 0.201$, $p < 0.05$) were also positive and supported $H_{6.}$

Table 5 Hypothesis testing results

Hypothesis	Relationship	Supported
H1	Consumers prefer voice for low involvement	Yes
	Voice and video for high involvement	
H2	Presentation format -> Trust	Yes
	Presentation format -> Usefulness	Yes
H3	Trust higher in voice presentation for low involvement	Yes
H3a	Usefulness higher in voice presentation for low involvement	Yes
H4	Trust -> Usefulness	Yes
H5a	Trust -> INTUSE	Yes
	Trust -> INTPUR	Yes
H5b	Useful -> INTUSE	Yes
	Useful -> INTPUR	Yes
H6	Trust -> USEFUL -> INTPUR	Yes
	Trust -> USEFUL -> INTUSE	Yes

4 Discussion:

The study delves into relatively underexplored areas of consumer behaviour and VAs. Firstly, it investigates how different presentation modes influence the trust and usefulness of VAs. Secondly, it compares various scenarios in which VA recommendations are trusted and

perceived as useful. Lastly, it reinforces the importance of trust and perceived usefulness in shaping behavioural intentions; intention to use a VA and the intention to purchase products using a VA.

As voice presentation has human-like traits, consumers treat VAs as social actors and perceive them as humans (Whang & Im, 2021). Building on this premise, it was hypothesized that voice presentation is likely to affect the trust and usefulness of VAs, which is expected to influence behavioural intentions. Additionally, this study examines the influences of trust via usefulness in VA, reflecting a pattern observed with online recommendation agents (Benbasat & Wang, 2005).

When consumers were asked about their preference for a low-involvement scenario, findings indicated a preference for the voice-only mode, emphasizing trust and usefulness over other presentation modes. For low-involvement products, consumers often look for limited details, and the voice presentation is able to meet this requirement. Conversely, for the high-involvement products, consumers found voice and visual mode to be useful and trusted as compared to voice-only mode. Given the high requirement for details, especially considering personal relevance, the voice and visual mode can provide the necessary details along with human-like traits in presentation. Hence, this becomes the preferred presentation format for the high-involvement product group. These preferences were supported by the ANOVA analysis results. Further, the results confirmed that the presentation format is likely to influence trust and usefulness. The significant interaction effect between presentation format and product involvement on trust and usefulness confirmed that voice-only was preferred in low-involvement scenarios, while voice and visual were preferred for high-involvement products. Additionally, it was found that trust had a significant influence on usefulness; thus, when consumers trust a VA, they are more likely to find the recommendations useful. The study also found that trust and usefulness are important predictors of behavioural intentions, intentions to use a VA, and intention to purchase using a VA. This is in line with previous studies done in the context of online recommendation agents (Benbasat & Wang, 2005; Jiang & Benbasat, 2007a; Qiu & Benbasat, 2008). The impact of trust on behavioural intentions is partially mediated by usefulness and supports H6. This confirms the mediating role of usefulness. This is not uncommon and previous studies in the context of technology adoption using TAM theory have established this relationship (Benbasat & Wang, 2005).

Chapter 4

Theoretical Contributions, Managerial implications, and Limitations:

4.1 Theoretical Contributions:

Essay 1

Our study's aim was to study the impact of exposure and task characteristics on preference to choose a chatbot. For this purpose, two experiments were conducted. In these two studies the respondents were exposed to positive and negative exposures and two levels of task complexity and time pressure of queries. This study found that consumers interact differently with the chatbots based on the task characteristics i.e., complexity and time pressure. Both studies confirm that exposure to chatbots under these situations reveal that for a non-complex and non urgent situations if the chatbots are able to resolve queries consumers perceived it as suitable for such task. When the exposure was negative, i.e., when the chatbots were unable to solve the query and redirected consumers to another channel they switch from chatbot to a more direct method, phone call in the context of this study. Under such situations consumers may anticipate more effort by first interacting with the chatbot and then moving to another channel. Therefore, under negative exposure they may prefer to connect with a human agent over a direct channel because there is a higher likelihood of query resolution.

However, when the exposures are positive, i.e., when the chatbots solve a query independently or in tandem with a human agent, the consumers' preference is likely to switch towards chatbots, they differed significantly for complex and urgent queries. In the pre-test for study 2, consumers preferred chatbots in the case of non-urgent and non-complex queries. However, post-test results found that task complexity is a critical factor in predicting future consumer preference to use chatbots than the time pressure of queries. In line with the previous research task complexity is the boundary condition for choice of AI customer service (Xu et al., 2020).

In case of the service design when chatbots employed by companies are not able to solve complex queries independently, whether they are urgent or non-urgent, they need human intervention to resolve complex queries. However, for non-complex queries, chatbots can resolve consumer problems without any human intervention for both urgent and non-urgent queries. Therefore, for complex queries, consumers may feel that interacting with a chatbot is a waste of their time and effort to interact with a chatbot as they have to depend on consumer executives for resolution ultimately. Even though chatbot technology is getting smarter,

consumers may have algorithm aversion (Dietvorst et al., 2015) and may still perceive that chatbots will be unable to solve queries independently and require human help. The findings of this study have important implications for theory and practice. Although this study makes significant theoretical and managerial contributions, this research has some limitations, which should be addressed in future research.

The study contributes significantly to various theoretical understanding in the area of consumer-chatbot interaction. It provides fresh insights into understanding consumer behaviour with chatbots for different types of consumer queries and their preferences to use chatbots. The study has contributed to the scarce literature by categorizing the consumer queries based on task complexity and time pressure by studying them as a task characteristic and TTF theory. Through this research, the study fills in the gap indicated by Xu et al. (2020) in understanding consumers' perception of task complexity. Time pressure is studied as a variable for the first time in the context of consumer queries and chatbots. It is one of the early studies to examine the role of the mere exposure effect, reverse mere exposure effect and its impact on consumers' preference to use the chatbot. This study demonstrates that task characteristics such as task complexity and time pressure are important drivers for using chatbots for customer service. The findings also highlight the importance of task complexity of queries in consumer satisfaction and their intention to use chatbots in the future. This study contributes to the tiered approach where chatbots are implemented first for customer service, with a subsequent option to escalate the query to manual customer service if required (Følstad & Skjuve, 2019; Grudin & Jacques, 2019). Our finding recommends that a tiered approach with a chatbot as an initial default option for non-complex queries is likely to increase consumer satisfaction and future use of chatbots. The finding also confirms with CASA paradigm, which states that computers are social actors and react to them as they would to humans (Nass et al., 1994; Nass & Moon, 2000). Under non-complex and non-urgent situations, the consumer may feel that chatbots would perform like human agents and reduce their time, effort, and cognitive load (Brachten et al., 2020). However, under complex situations need for human interaction is higher (Anton, 2000); therefore, interacting with chatbots is not as satisfactory as in the case of non-complex conditions and would prefer to use human help.

Essay II

The study has significant theoretical contributions in the area of voice assistants and consumer behaviour. Essentially, with the help of ELM and CASA framework the study

highlights the importance of presentation format and product involvement play an important role in the product search and consumer's purchase decision. The study has examined influence of three presentation formats under different levels of product involvement. While recent studies in the context of VAs for product search have examined the effects of modality such as touch and voice (Pagani et al., 2019) text vs voice (Flavián et al., 2023; Rzepka et al., 2021) the combination of voice and visual presentation which is extensively used in real life has surprisingly received very little attention so far. By including this format, the study furthers the understanding of consumer behaviour in the context of voice assistants. This research contributes to the gap in the existing literature by putting together the different types of presentation formats and different levels of product involvement. It has attempted to understand perception of consumers such as trust and usefulness under various presentation formats. As suggested by previous literature involvement plays an important role in product search using VAs. The findings show that voice presentations are more useful in case of low involvement products as compared to high involvement products. Voice presentations are able to provide customers with concise and relevant information, which suits low involvement product search. On the other hand, visual presentations are able to give detailed information that is more suitable for high involvement product.

Furthermore, the study highlights the important role of trust and usefulness in determining consumer behavioural intention such as intention to use a VA for product search and purchases. Trust had a significant influence on usefulness indicating that when consumers trust a VA, they find the suggesting to be useful. By using the lens of ELM to develop the conceptual framework, the study has attempted to answer the call raised by Shahab (2021) to use ELM theory in the context of VAs.

4.2 Managerial implications:

As pointed out in the introductory section and also Chapter 2 and 3 of the study as this is a new and emerging research area the finding should be able to clarify areas for the use of AI tool. With respect to the chatbot, the results of the study will throw light on how the complexity of queries determines the use of chatbots for customer service. Based on the hypothesis the low complexity queries are the ones where customers are likely to prefer a chatbot. For a complex query, customers may still prefer a direct channel or prefer to speak

to a human agent. The results are likely to support the tiered system followed in customer service where the query is initially posed to a chatbot and escalated to a human executive in case the chatbot is not able to resolve it independently (Følstad & Skjuve, 2019; Grudin & Jacques, 2019).

Essay 1, The findings of this study help in understanding consumer behaviour and preference to use AI tool and therefore have important implications for managers who are considering implementing chatbots in their customer service operations. The study highlights the importance of considering task complexity and time pressure when deciding where and how to use chatbots.

Managers can use the tiered approach suggested by the study to first implement chatbots for non-complex queries, which are likely to be resolved quickly and easily. This can increase consumer satisfaction and save time for both consumers and customer service representatives. For more complex queries, managers can implement chatbots that are able to handle a wider range of issues, but with an option for consumers to escalate to human intervention if necessary.

The study also suggests that negative experiences with chatbots can lead to a preference for human interaction, particularly when consumers anticipate more effort. Managers can use this information to ensure that chatbots are appropriately designed and trained to handle consumer queries, and that human intervention is available when necessary.

Overall, the study can help managers make more informed decisions about how to use chatbots in their customer service operations, which can lead to improved consumer satisfaction, reduced workload for customer service representatives, and potentially even cost savings.

Essay II

With growing importance of voice in the area of product search and purchases, it is important to understand what are the situations where consumers would be motivated to use a VA. As reading and listening have different impact on consumers (Rzepka et al., 2021), the information processing guides their decision making (Munz & Morwitz, 2019). The findings

of the study have some important implications for business managers intending to use voice medium to assist consumers in their product search and purchase. Voice presentation can offer benefits over other presentation format as it is quick, easy to understand and operate. However, the conditions in which voice could be employed to serve customer should be carefully examined. Employing voice to serve customers could simplify the process of searching the products by highlighting important features, product ratings and other essential product descriptions. This could help consumers make favourable decisions. When the VAs present search results in a humanized auditory mode consumers find this useful especially for low involvement products. However, the voice presentation may not be perceived as useful in high involvement products due to the requirement of detailed information. For low involvement products consumers prefer to spend less time, as they are routine and frequently bought products (Rhee & Choi, 2020; Zaichkowsky, 1985). In addition, the research findings highlighted the role of trust and perceived usefulness in influencing intention to use the technology and intention to purchase using a VA. This is likely to influence intention to use and intention to purchase. Trust and usefulness are important predictors hence managers should work in building trust to enhance perception of competence. Since the research also establishes the influence of trust on usefulness it is imperative for managers to build trust.

4.3 Limitations:

Essay I

The study presented a phone call as an option because a phone is comparable to a live chat, and many companies in the real world provide phone calls as an alternative option to a chatbot. However, phone calls as an option is not explored as a detail. Future studies can do a comparison of both the channels for different queries, and outcome variables such as satisfaction and engagement can also be considered. Only two variables for classifying the customer queries: task complexity and time pressure were considered in this study. Future research may also include other variables to classify the customer queries. Future researchers could replicate the findings with real chatbots offered by companies in a field study, which will improve the study's external validity. Understanding consumer preferences for chatbots could further be strengthened by undertaking a longitudinal study that would help understand consumer behavior over a period of time. The impact of personalization on the choice of AI tools is another area where this study could be extended. The trust with privacy issues also

impacts the choice of AI tools and thus could be an area to explore. Customer attributes could play an important role and could be considered for future studies.

Essay II

The study has some limitations and therefore could be a fertile area for future research. In this research the role of presentation formats on trust and usefulness was examined. As this was an experimental design only few variables were considered. Future studies could also examine the role of personal innovativeness of individual consumers as it plays an important role in adopting technology. Understanding how personal innovativeness could influence interactions with VA could be add to the user behaviour in this area. Frequent use of voice only mode could reduce the dependence on visual prompts for consumers, this could further change the buying behaviour. Thus, longitudinal studies could be undertaken to study the impact of voice only mode on consumers and their attitude towards other modes of shopping. Personalization is an important feature, the recommendations given by VAs are guided by consumers previous search and could be highly personalized hence personalization offered by the VA could be considered as another variable in the model. Further comparative studies between VA and online website shopping could help to understand consumers to VA in terms of convenience and guidance. Future studies could manipulate different levels of intelligence of a VA to understand how consumer respond and interact with a VA. Localization could also play an important role in following recommendation of the VAs. It would be interesting to know if localization moderates the intention to follow a VAs recommendation, future studies could explore this aspect further.

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